A two-stage bid-price control for make-to-order revenue management

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1. Introduction

Companies, which use make-to-order (MTO) order fulfillment strategies, face the problem of accepting or rejecting dynamically arriving customized orders that are unique to the customer. In checking customer orders against limited capacities, available-to-promise (ATP) approaches provide support for this decision situation. ATP concepts are widely implemented in industry and are available in commercial tools for planning and scheduling. However, ATP fails to provide decision support when demand exceeds capacity. In such a situation, companies have to decide which orders to accept and which orders to reject in order to maximize profits. Customer requests should therefore be evaluated with respect to the opportunity costs of their acceptance. In assessing the order's utilization of bottleneck capacity, revenue management approaches satisfy this requirement and can thus be used to complement ATP [1,2]. The associated business function is referred to as capacity control.

Within the last years there is an increasing emphasis on incorporating capacity control concepts into the order acceptance process of MTO companies. For medium term capacity allocation decisions, approaches based on expected marginal revenue analysis have been successfully applied [3]. For short term sales, bid-price approaches are amongst the most popular instruments [4]. The most important reason for their popularity in MTO revenue management is that bid-price based approaches neither require customer requests to be standardized in terms of capacity requirements nor to arrive in a predetermined sequence, both of which holds true for MTO production. A threshold price, the bid-price, is computed for each bottleneck resource. This price reflects the opportunity cost of consuming one unit of capacity. Orders are accepted, if the associated revenue exceeds the opportunity cost of their specific resource requirements. Details on bid-price approaches and other revenue management methods can be found in [5,6].

The determination of opportunity costs requires knowledge on the optimal allocation of capacity. This allocation can be determined using mathematical programming based on the forecast on the demand to come. However, forecasting demand in MTO settings is challenging. This is on the one hand due to the variety of the product offering, which easily comprises several thousands of configurable products and on the other hand due to the volatility of demand, which is more pronounced than in mass markets. To account for this uncertainty, bid-prices may be re-computed with respect to previously accepted orders and current demand information [7,8]. While this procedure is widely employed in service industries where transactions are highly standardized (e.g. one seat on a flight connection), there are limitations with respect to MTO settings. Firstly, sales management commonly requires simple ways to track
the acceptance decisions of the sales personal [9]. In many cases the sales performance is assessed with respect to a reference price. If bid-prices are used as reference prices, they should not be changed frequently not to cause serious dynamics into the sales organization. Secondly, MTO sales are usually not executed online. Customers are requesting for an offer and are confirming this offer after a consideration phase. If bid-prices are updated in between, consistency issues appear. Despite volatile demand it is consequently not surprising that MTO revenue management approaches focus on the application of static bid-prices, which are not changed throughout the booking period [10]. Accordingly, consistency issues arise. If the real demand deviates from the forecast, the application of the (wrong) static bid-price results in inferior order acceptance decisions.

To account for this drawback of static bid-prices, we introduce a two-stage procedure, which combines anticipative with reactive elements. Demand information is collected within the first stage, using a static basis bid-price which is set in anticipation of future demand. In the second stage, the bid-price is updated, in response to new demand information. Limiting the number of updates allows for the transparent and stable coordination of the sales organization, which in contrast to purely static approaches still incorporates current demand data. Compared to reactive re-computation, planning nervousness is reduced, since updates are deferred until sufficient demand information is available. At the same time, the future flexibility to change the bid-price is explicitly considered, when determining the basis bid-price.

Capacity control models which combine anticipative (static) elements with reactive (dynamic) ones are becoming increasingly popular. The underlying problem can be formulated as a dynamic and stochastic knapsack model. Exact solution approaches to this model are based on stochastic dynamic programming and have been studied by Talluri and van Ryzin [11] and Kleywegt and Papastavrou [12]. However, these approaches become computational intractable, when practical problem sizes are considered [8,13]. To cope with the computational burden, several heuristic approaches have been proposed. These can be classified into two classes according to the frequency bid-prices are updated [14]. The frequency ranges from request-based updates, which allows for the continuous adoption of the bid-prices with each customer request, to time-based approaches, restricting updates to one or multiple points in predefined intervals.

The most accurate approximation of the MTO capacity control problem is based on request-based updates. A heuristic approach based on simulation optimization, entitled self-adjusting bid-prices, has been introduced by Klein [7]. To account for forecasting errors, linear functions are applied, which continuously adjust the bid-prices with respect to the total capacity booked and the expected booking or the elapsed time, respectively. However, the approach is computationally intensive, even if the bid-price updates are limited to linear functions.

To reduce complexity, time-based adjustments are proposed in the literature which limit bid-price updates to predefined points in time. In [4] a concept of dynamic bid-prices on the basis of dynamic programming is developed. Instead of static values, a time trajectory of bid-prices is computed in advance. Bid-price updates are defined purely anticipative dependent on the time elapsed. Current demand information is not taken into account. In another group of papers, formulations based on multi-stage stochastic optimization are used [15,16]. Multi-stage approaches can significantly outperform static ones. The computational burden, however, imposes tight boundaries on real-world applications. To address this issue, Chen and Homem-de-Mello [17] present an approximation to the multi-stage formulation, solving a sequence of two-stage problems with simple recourse.

The major barrier to the implementation of the latter approaches in MTO settings arises from the fact that bid-prices are updated frequently. By limiting the updates to a single change, two-stage approaches better comply with the requirements of MTO-production as mentioned above. Additionally, the complexity is reduced, allowing for MTO capacity control problems of relevant size to be solved. The basic idea is to fix one part of the decision variables (bid-price of the first stage) before the actual realization of uncertain parameters (demand) occurs. The variables are adjusted after the random event (demand) becomes well predictable. Two-stage approaches have been proposed by e.g. De Boer et al. [18] and Higle and Sen [19]. The computational burden of incorporating exact information on the distribution of uncertain demand parameters is still challenging such that approximations become necessary [20]. This in particular holds true, if other than idealized demand distributions have to be considered. In this case, typically sampling methods are used to construct scenario trees [16]. In the case of MTO manufacturing, both demand volume (number of orders) and demand structure (contribution margin and capacity requirements of the orders) are uncertain. To define a certain state in the state space, multiple parameters are necessary. The resulting scenario trees are thus subject to the well known curse of dimensionality. The approach developed in this paper is likewise based on sampled demand data. However, we omit the generation of scenario trees and present a search procedure to determine the basis bid-prices. This procedure is based on demand scenarios in order to approximate the underlying stochastic process. Accordingly, demand variability can easily be incorporated. To determine bid-price updates, we apply techniques from artificial intelligence, namely neural networks.

The objective of this paper is to develop a revenue management approach, which provides decision support in order acceptance for the specific needs of MTO companies. We focus on spot market sales, which are placed on short notice and on a nonrecurring basis [21] and assume a single bottleneck resource. The proposed approach differentiates itself from the literature on MTO revenue management by updating the selection criteria at a predefined point in the booking period. As opposed to other re-computation approaches, the updating option is explicitly considered when computing the bid-price for the initial stage. The most important feature is that we use neural networks to compute the update. In doing so, we are able to incorporate both the non-linear characteristics of bid-prices and multiple inputs signals to characterize demand. The contribution of this paper is threefold: (1) description and analysis of information dynamics and its impact on the capacity control policies of MTO companies, (2) development of a new two-stage bid-price policy for capacity control, (3) evaluation of the performance of the developed policy with respect to expected contribution margin and risk. The organization of the paper is as follows. In Section 2, we introduce the problem setting, including information dynamics, which lays the motivation for our approach. In Section 3, we present our conceptual approach, which distinguishes an offline and an online phase. Neural networks are implemented to adjust the selection criteria after the offline phase. In Section 4, results from a computational study are provided. This study reflects the main characteristics of real-world MTO production in the steel industry. Section 5 concludes the paper with an outlook on future research issues.

2. Order acceptance in MTO-production

2.1. Problem setting

We consider the order acceptance problem of a company which uses a MTO order fulfillment strategy and faces excess demand. The company operates a single bottleneck resource, e.g. capital intensive machinery. Spot market sales are considered...
such that for every booking period (e.g. one week) there is a defined production period of the same length [10]. Thus, time can be divided into a sequence of non-overlapping periods as illustrated in Fig. 1.

We assume capacity to be fixed. Since production activities are strictly linked to customer orders, capacity is lost if it is not sold at the end of the booking period. Orders arrive dynamically over time in the period \([0, T]\). Each order \(i\) is characterized by specific requirements of bottleneck capacity \(a_i\) and an ordering date \(o_i\). Unlike the airline case where low value demand typically arrives before high value demand, order arrivals on the spot market are random [1]. Due to significant variable costs encountered in MTO manufacturing, it is insufficient to consider the revenue of an order. The contribution margin \(p_i\) has to be considered instead. Both revenue and contribution margin are order specific. Assuming the absence of systematic forecast errors the demand process is modeled by distribution functions describing total demand, ordering date and contribution margin.

The objective of the capacity control policy is to best utilize the bottleneck capacity. Accordingly, those orders are to be selected that in total yield the highest contribution margin. The specific challenge is that the informational basis is evolving over time. This characteristic is called informational dynamics [22] and is elaborated in the following section.

### 2.2. Information dynamics

The specific challenge of capacity control in MTO settings is that decisions about the acceptance or rejection of orders have to be made with incomplete knowledge, i.e. before all orders have been placed. The uncertainty decreases, the higher the share of already known orders. To illustrate this effect, we can refer to the following example. Considering one booking period \([0, T]\), MTO ordering processes for a single period of production can be described by three distribution functions regarding the number of orders, i.e. how many orders are placed, the ordering lead time, i.e. when are the orders placed, and the order characteristics, i.e. capacity requirement and contribution margin. If the lead times are assumed to be normally distributed and constrained to the interval \([0, T]\), the number of orders is assumed to follow a Poisson distribution and the order size is modeled by a triangular distribution, we obtain results as illustrated in Fig. 2. Depicted is the cumulated capacity requirement of all orders placed within the booking period, i.e. at \(t=T\), plotted versus the cumulated capacity requirement of those orders which are placed until a specified point in the booking period \(t=t^*\). Every single point represents one demand realization, each of which is generated by drawing random numbers from the above mentioned distributions. In total, 1000 data points are considered.

As can be seen from the analysis, there is an interrelation between the cumulated capacity requested up to the defined point in time and the total requested capacity at the end of the booking period \((t=T)\). Obviously, this relationship is perfectly linear at the end of the booking period (indicated by \(R^2=1\)). A similar pattern can be obtained when the analysis is conducted at two thirds of the booking period \((t=2T/3)\). However, considering the situation after one third of the booking period \((t=T/3)\), there is hardly any interrelation \((R^2=0.11)\).

With respect to the implementation of reactive approaches, these findings are crucial. Updating the bid-price early in the booking period cannot result in major improvements. The underlying reason is that there is no substantial change in the informational basis. Even worse, changes to the bid-price have to be revised later on, when better information is available. As a consequence, the planning nervousness would increase. However, the situation is different at two thirds of the booking period. At this point, the shape characteristics inherent to the final shape can be identified. Adjusting the bid-price thus seems to be promising.

However, while the informational basis improves over time, the demand to come decreases: the later the change is made, the smaller the number of orders which can be selected using the updated criteria. This trade-off is illustrated in Fig. 3. The same
assumptions hold true as given above. Depicted is the explanatory power $R^2$ on the one hand and the share of remaining demand which is expected to come, on the other hand. The earlier the update occurs, the larger the potential to increase the total contribution margin but at the same time the higher the uncertainty. This trade-off has to be solved for practical applications.

Given these findings, capacity control approaches which monitor the demand stream for some period of time and update the selection criteria using this demand data seem to be promising.

3. Two-stage bid-price approach

3.1. Concept

Motivated by the data analysis in the previous section, we propose a new approach, which capitalizes on the correlation between the observed demand during the booking period and the final demand level at the end of the booking period. The bid-price is updated at a predefined point during the booking period, where the explanatory power of the available online demand data is sufficiently strong to predict the final demand level with a high degree of certainty.

The proposed framework is visualized in Fig. 4, depicting the different stages within the booking period $[0,T]$. The timeline is divided into two stages by the point in time $t^*$ where bid-prices are adjusted. Until $t^*$, a basis bid-price $BP$ is applied. In the second stage, from $t^*$ until the end of the booking period $T$, a realization specific bid-price $BP_j$ dependent on the particular demand realization $j$ is applied. Both $t^*$ and $BP$ are determined ex ante, anticipating future demand fluctuations whereas the realization specific bid-price is set in reaction to updated demand information. The combination of both stages yields a hybrid approach which combines both anticipative and reactive elements.

The general logic is illustrated in Fig. 5. If the demand observed until $t^*$ suggests a high total demand for the end of the booking period, the bid-price is increased. As a result, the selectivity of the capacity control policy is reinforced. However, when the demand observed until $t^*$ suggests a low total demand, the bid-price is lowered.

To implement the proposed approach, four components are required. These can be separated into online and offline functionalities. Offline functionalities are performed before the actual booking period starts and online functionalities are performed during the booking period, accessing the current demand data. The determination of $t^*$ as well as the calculation of $BP$ belong to the offline functionalities. Online functionalities are the classification of the current demand realization and the calculation of the demand realization specific bid-price $BP_j$. In the following section, the online and offline procedure are described in detail.

3.2. Offline procedure

The objective of the offline procedure is to set the general parameters of the approach. It is performed using the anticipated demand information, before the booking period starts. The task is both to fix the interval boundary $t^*$ and to determine the basis bid-price $BP$.

The main determinant of the information dynamics which governs the choice of the interval boundary $t^*$ is the distribution function of the ordering lead time. This function determines the share of known orders at any point in time and thus the accuracy of the informational basis. Even if demand can be modeled as an ideal Poisson process, determining the optimal value for $t^*$ is impractical. Thus heuristics become necessary [17]. For the sake of simplicity, we assume an interval boundary which is set exogenously.

The basis bid-price $BP$ is used to accept orders in the anticipative order acceptance stage. In the following we present a scenario based approach to efficiently determine the optimal value of $BP$ for the proposed bid-price control ($BP^*$. The search procedure is motivated by the fact that the total (expected) contribution margin is a convex function over $BP$. This can be explained by the following simple reasoning: if $BP$ is set too low, too many low value orders are accepted such that later arriving high value orders have to be declined due to the fixed capacity. This number decreases as $BP$ is raised, contributing towards an increase in the total contribution margin. This effect holds on until $BP^*$ is found. A further increase in the $BP$ causes a capacity control which is too selective. Consequently, orders which should
have been accepted are rejected. The total contribution margin decreases. Note that $BP^n$ is not necessarily unique. A range of bid-prices may result in the same optimal order acceptance policy, if a limited number of very heterogeneous products is considered [11]. In MTO production, an arbitrary number of products may be produced. This suggests the existence of a unique value for $BP^n$. Independent on the uniqueness, knowledge on one $BP^n$ is sufficient for the presented approach, since all optimal bid-prices result in the same order acceptance policy.

As a result, to determine $BP^n$, an enumeration procedure can be employed, which is based on the principle of a hill climbing search. To incorporate stochastic demand information, simulation techniques are appropriate to generate demand scenarios. Following these ideas, the search procedure yields the basis bid-price, which optimizes the total expected profit. In addition, data on the demand realization specific bid-prices $BP_j$ is generated, which is used to support decision making in the reactive second phase, as elaborated in the following section.

The pseudo-code representation of the enumeration procedure is given in Fig. 6. The procedure is based on the data of possible demand realizations. Given a historical order record and a forecast, this information can be readily generated using simulation [10]. The general logic of the search procedure is to estimate the total contribution margin of each $BP$ using the data of $R$ demand realizations (2) and to increment $BP$ until the objective value decreases the first time (1).

In the evaluation phase, at first, all orders are initially assessed in the sequence of their arrivals and are either accepted, if the bid-price and the capacity condition are fulfilled, or are saved to the set of orders $F$, if they arrive after the interval boundary $t^n$ (3). After sorting the orders of the set $F$ according to their specific contribution margin (4), the demand realization specific bid-price $BP_j$ is determined (5). To this end, orders are accepted until the capacity is filled, assuming ex-post knowledge. The specific contribution margin of the last accepted order determines the marginal value of the capacity and therefore the bid-price for a particular demand realization. If the capacity requirements of all orders do not fill up to capacity, the bid-price is set to zero. The iteration is continued, until all demand realizations are evaluated. To estimate the expected performance of a certain $BP$, the average total contribution margin of all demand realizations is computed (6). Lastly, the performance of the current value of $BP$ is compared

![Fig. 6. Offline enumeration procedure.](image-url)
with the previous (7). In case of an improved performance, the procedure is continued with the next value of $BP$ or ended otherwise. The basis bid-price $BP^*$, which result in the maximum contribution margin for the search space, is selected to be used in the first phase of the proposed approach.

### 3.3. Online procedure

In the online procedure $BP^*$ is adjusted in accordance with the specific demand realization. The objective is to provide an improved estimate on the total expected demand that can be used to determine the appropriate bid-price to be applied in the remainder of the booking period.

In designing the online procedure, information on the general structure of bid-price controls proves helpful. As long as the cumulated remaining demand for a booking period falls short of remaining capacity, all remaining orders should be accepted. The optimal bid-price thus computes to zero. Only if the cumulated remaining demand of a booking period exceeds remaining capacity, a positive bid-price occurs. In the idealized case of a uniformly distributed demand structure in terms of price, bid-prices would be linearly increasing with the demand volume exceeding capacity as depicted in Fig. 7. Accordingly, there is an inherent unsteadiness in the bid-price function. To address this general characteristic of bid-price based revenue management, a two-stage procedure is proposed.

The aim of the first step is to determine whether the updated demand estimate surpasses the available capacity. This results into a classification task. If the demand scenario is classified as “demand below capacity”, the scenario specific bid-price $BP^*$ should be set to zero. If the scenario is classified as “demand above capacity”, the bid-price is adjusted in a second step. The two functions classification and adjustment result in two models.

Most existing multi-stage approaches are based on some explicit representation of the state space to define the bid-price update. The limitation of these modeling approaches arises from the tremendous size of the state space, if configurable products are considered. Since in MTO-production both, capacity requirements and the contribution margin are order specific and therefore stochastic, the size of the state space easily becomes intractable. To avoid this limitation, we present a neural network approach to model the state space implicitly and use the information from this approach to adjust the bid-price accordingly. The advantage of neural network is that they are capable of modeling the non-linear relationship between the bid-price and the expected demand which occurs if other than uniform demand distributions are considered. Further, the optimal bid-price value is not determined by one single demand characteristic. Using neural networks, information on the multiple demand characteristics such as the volume and the value can be incorporated simultaneously.

The integration of neural networks into the proposed bid-price approach as well as the details on the implemented neural networks are discussed in the following section. To the best of our knowledge, this is the first study applying neural networks in MTO revenue management.

### 3.4. Integration of neural networks into the online procedure

Neural networks are modeling tools that consist of an interconnected group of processing units called neurons or nodes, which mimic the principle of biological neurons. Each unit receives inputs from other units via weighted connections and generates an output which is passed on to other neurons [23]. Neural networks can be trained by empirical data to approximate the function between the inputs and outputs and are capable of generalizing to new data. Due to their characteristics of non-linearity, massive parallelism, robustness and ability to learn, neural networks are in general well suited for problems with limited theoretical richness but high data richness [24,25].

Multilayered feedforward neural networks which use the backpropagation training algorithm [26], namely backpropagation networks, are amongst the most popular neural network models and are used in this paper due to their effectiveness and simplicity. Using hill search and supervised learning with a feedback loop in the form of an error function, the set of connection weights is adjusted to optimize performance for a specific application [26,27]. The architecture of these networks is defined by the number of hidden layers, number of nodes in each layer and transfer functions of each neuron. Using a single hidden layer and sufficiently many nodes, neural networks can approximate any continuous function to any degree of accuracy [28,29].

In response, backpropagation network structures with one hidden layer are applied in the following. A schematic representation is provided in Fig. 8 where circles represent neurons and arrows the weighted connections. The neurons are organized into layers and signals are passed from the input layer to the output layer through the hidden layer [27].

To model the discontinuity of the bid-price, two models are required. The first model, *Neural network I*, is necessary for the classification task and a second model, *Neural network II*, for the bid-price adjustment.

To train the networks, data on possible demand scenarios and the associated bid-prices $BP^*$ is required. The data obtained from the offline phase (Section 3.3) fulfills this requirement. To incorporate information on both, demand volume and demand value, two input signals are necessary. We will in the following use the observed demand (1st signal) indicating the demand volume and the booked demand (2nd signal) defining those orders with high value. As the desired output of *Neural Network*...
than zero) is given to the network. All scenarios with positive \( BP_j \) are considered to train Neural Network II. Again, both inputs are used together with the ex-post optimal bid-price values, which represent the desired outputs. To prevent "overfitting" during training, stopping rules are applied. Other design parameters include the learning rate, controlling the step size in the updating process during training, and the momentum coefficient, which controls the influence of the previous updating step on the current one and are given in the next section. For further information on the influence of the different design parameters, the interested reader is referred to [25].

The process to integrate both neural networks into the online procedure is presented in Fig. 9. Based on the trained networks and scenario specific information on the observed and the booked demand, the scenario specific bid-price \( BP_j \) is determined in a two-stage procedure. In the following the results of a computational analysis are presented.

4. Computational study and results

The performance of the proposed two-stage bid-price updating approach using neural networks (BPU-NN) is evaluated in a computational study based on a simulation model reflecting the main characteristics of a high performance steel manufacturer, similar to those reported in [30]. Results are generated for four different demand settings, which result from the combination of two demand levels and two volatility levels. We used two kinds of benchmarks policies to evaluate the approach. On the one hand, existing capacity control approaches are considered. To mimic current practice in the steel industry, we used a first-come-first-served policy (FCFS) as a benchmark. Using FCFS, orders are accepted, if their contribution margin is positive and sufficient capacity is available. In addition to that, we compared the results to those of well established revenue management methods such as randomized linear programming without (RLP) and with re-solving at \( \tau^* \) (RLP-R). On the other hand, we incorporated two idealistic benchmarks which reflect upper bounds on the contribution margin. As a first idealistic benchmark, we solved the capacity control problem ex-post, assuming perfect hindsight (EP). As a second idealistic benchmark, a modification of this policy was used to assess the effectiveness of the proposed bid-price updates (BPU-EP). To this end, we computed the results which would have been obtained, if the \( BP^* \) was applied for the first phase and realization specific ex-post optimal bid-prices for the second, i.e. after \( \tau^* \).

4.1. Simulation model

The simulation model represents the order acceptance process of a high performance steel manufacturer with a single bottleneck resource. This might be capital intensive machinery like an annealing oven. To model demand, some assumptions regarding the number of orders, their contribution margin (\( \epsilon \)), lead time (days) and resource requirements (hours) are necessary. Historical data from a high performance steel manufacturer served as input to fit the distributions.

It is assumed that the order arrival process in the system follows a Poisson process with a mean arrival rate of \( \lambda = 400 \) orders per booking period for the 100% demand level. A 100% demand level represents the case, where on average, demand can be completely fulfilled by the capacity of the resource. Booking and production period are set to 30 days each. Capacity of the resource is fixed at two shifts of eight hours a day, hence 480 h of capacity are available per production period. Lead times measured in days were generated following a normal distribution \( N(15, 25) \). Since only nonnegative lead times are feasible, the distribution is truncated at 0 as well as at 30 to keep an unbiased mean and stay within the length of the booking period. Whenever these boundaries are violated, it is re-sampled. Capacity consumption per order (hours) is sampled from a triangular distribution with a minimum value of 0.1, a mode of 0.5 and a maximum of 3.0, resulting in 1.2 as mean value. The contribution margin (\( \epsilon \)) of an order was generated according to a lognormal distribution with log mean of 9000 and log standard deviation of 12,000.

Two demand levels 110% and 125% are considered, representing the case of 10% and 25% excess demand. These demand levels are simulated by adjusting the Poisson order arrival process to \( \lambda = 440 \) and 500, respectively. Further, two volatility levels are generated: a high volatility case for which the triangular distribution for the capacity requirements per order is applied as described above and a low volatility case for which a point estimator (the mean capacity requirement) is applied. Using a constant capacity requirement per order represents an unrealistic assumption in MTO settings, but allows for general insights into the effectiveness of the approach. In addition, it resembles the basic airline case, where each booking consumes the same amount of capacity, namely one seat. Thus, more general conclusions can be drawn.

BPU-NN was implemented with neural networks using one hidden layer and non-linear sigmoidal type transfer functions. The number of nodes for the networks is provided in Table 3 in the appendix. As input information for the neural networks we used the observed demand and the booked demand information. Inputs are normalized to lie in the range 0 to +1.
BP was computed using the demand data of 1000 demand scenarios. Based on a pre-analysis, the point in time where the \( BP_t \) is adjusted was set to \( t^* \approx 20 \) days. Training data of the neural networks is based on the same 1000 demand scenarios. The problem of overfitting was addressed by applying a cross validation stopping rule. Training was terminated when the mean squared error on the cross validation set began to increase or a maximum number of training epochs was reached. Of the 1000 demand scenarios, 60% were consumed for training, 20% for testing and 20% for the cross validation set. A learning rate of 0.1 and a momentum coefficient of 0.7 were applied.

Concerning the implementation of the traditional revenue management methods, RLP bid-prices are based on the same 1000 scenarios used for training the neural networks and are kept static. To implement RLP-R, the static RLP bid-price is applied until \( t^* \) and then re-computed using information on remaining expected demand and remaining capacity. For re-computation we used 100 demand realizations. Resulting bid-prices are provided in the appendix in Table 4.

The simulation was implemented in Plant Simulation 8.1, mathematical models were coded in LINGO 10 and the neural networks were developed using NeuroSolutions 5.

4.2. Results

In this section, we present the results of a numerical analysis. We distinguish three parts. The focus of the first part is on the expected performance. This analysis is complemented by a second part, focusing on the sensitivity of the results with respect to the main parameters elaborated in Section 3.2. Lastly, the potential of the approach to support risk-averse decision making is analyzed. Results are based on 200 demand realizations (arrival processes). We used common random numbers as a variance reduction technique.

4.2.1. Performance

The average total contribution margin normalized to the average of a FCFS policy is provided in Table 1. Corresponding paired t-test results are presented in the appendix in Table 4.

According to the results, BPU-NN outperforms the benchmark policies across all demand settings. Applying a FCFS policy leaves 8.2% to 21.4% of the revenue potential untapped. The RLP bid-price approach as well as RLP-R realize a significant portion of the remaining gap. In all demand settings, BPU-NN performs better than the traditional bid-price methods RLP and RLP-R for a 95% level of confidence. Moreover, the small gap between EP and BPU-EP shows that one adjustment captures nearly the complete revenue potential.

With respect to the worst case of all demand realizations BPU-NN falls 9.5 percentage points short on the EP (110%, LV). Generally this gap is significantly smaller. Across all demand settings considered, in at least 96 percent of all realizations the performance deviates not more than five percent from the ex-post optimum.

In order to shed light on the influence of volatility, we included two further demand settings into the analysis. To this end we enlarged the intervals the orders’ capacity consumption was sampled from by factor five (very high volatility) and factor 10 (ultra high volatility). The results structurally matched those reported in Table 1. We conclude that volatility does not impact the relative performance of the analyzed capacity controls.

4.2.2. Sensitivity analysis

To investigate the sensitivity of the results, we systematically varied the values for the interval boundary \( t^* \) and the basis bid-price \( BP \). The step size used was 1 for \( t^* \) and 100 for \( BP \). To keep the analysis tractable we refer to the results of BPU-EP, defining an upper boundary for the performance of BPU-NN. The resulting surface plots are depicted in Fig. 10. Results are scale transformed with respect to EP and FCFS. A value of 100% indicates a performance equal to EP, a value of zero a performance equal to that of FCFS.

Obviously, a performance close to EP is obtained, if \( BP \) is switched to its scenario specific optimal value early in the booking period \( (t^* < 5) \). This finding holds true, regardless of the value of \( BP \), the volatility level and the demand level. As opposed, the performance comes close to FCFS, if the \( BP \) is set to a very low value \( (BP = 100) \) and the interval boundary \( t^* \) is set to a value higher or equal to 25 for the 110% demand level. In this case the scale transformed improvement is less than 1%. The underlying reason is that basically no order is declined. Capacities are therefore on average close to be filled, when the bid-price is updated to its optimal value. This effect is even more pronounced for the 125% demand level. Since capacities fill up faster, the critical value of \( t^* \) is reduced to 22.

There is a risk of on average performing worse than FCFS, if a high value for \( t^* \) is combined with a high value for \( BP \) and the 110% demand level. The underlying reason is that too many high value orders are declined before corrective action is taken. For the high demand level the effect is reduced, since overall more orders enter the system. Note that we were not able to identify a performance worse than FCFS for the parameters considered in the analysis for the 125% demand level.

If \( BP \) is set close to its optimal value \( BP^* \), the results indicate a performance which is rather insensitive to the interval boundary \( t^* \). The results indicate the highest sensitivity for the low variability 110% demand level, for which the scale transformed

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\text{Table 1: Contribution margin relative to FCFS’ average for different demand levels (DL) in percent (} t^* = 20\text{).}
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<td>Min</td>
<td>86.6</td>
<td>82.9</td>
</tr>
<tr>
<td>Max</td>
<td>122.0</td>
<td>116.5</td>
</tr>
<tr>
<td>RLP Average</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>91.6</td>
<td>95.7</td>
</tr>
<tr>
<td>Max</td>
<td>129.1</td>
<td>138.5</td>
</tr>
<tr>
<td>RLP-R Average</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>91.7</td>
<td>96.5</td>
</tr>
<tr>
<td>Max</td>
<td>130.3</td>
<td>142.5</td>
</tr>
<tr>
<td>BPU-NN Average</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>91.5</td>
<td>96.0</td>
</tr>
<tr>
<td>Max</td>
<td>132.1</td>
<td>144.0</td>
</tr>
<tr>
<td>BPU-EP Average</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>91.5</td>
<td>96.0</td>
</tr>
<tr>
<td>Max</td>
<td>133.4</td>
<td>144.3</td>
</tr>
<tr>
<td>EP Average</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>92.5</td>
<td>97.5</td>
</tr>
<tr>
<td>Max</td>
<td>134.2</td>
<td>145.3</td>
</tr>
</tbody>
</table>
The focus of the analysis carried out so far was on risk neutral decision makers. A capacity control policy is perceived best, if it on average results in the highest contribution margin. However, the performance falls short on BPU-NN. The results of a risk analysis are given in Table 2 and Fig. 11. Depicted are the results of the BPU-NN policy compared to RLP, RLP-R and BPU-NN for the 110%, low volatility demand level. Even with non-optimal basis bid-prices, BPU-NN yields average results which are better than those of RLP and RLP-R. However, the performance falls short on BPU-NN. The results of a risk analysis are depicted in Fig. 11. The risk associated with the selected BPU-NN policies. For selected BPU-NN policies.

4.2.3. Risk analysis

The basic idea is to construct a trade-off curve between profit and risk [33]. In MTO revenue management, risk can be considered as performing worse than FCFS. To manage risk the value of BP in the first phase can be gradually decreased, lowering the selectivity of capacity control. In the second phase, the realization specific bid-price is used to adjust the selectivity with respect to the updated demand information. Thus, it serves to partially compensate for BP set too low for the particular demand realization. The associated policy is denominated BPU-NN, for BP set v units below the optimal basis bid-price BP of a risk neutral decision maker.

To quantify risk we use a downside risk measure, the loss function LF [34]. The LF standardizes the cumulated negative deviations to FCFS with respect to the cumulated contribution margin of the FCFS policy. Let M denote the revenue management policy and SC the demand realization from 1 to SCmax, then the loss function is defined as

$$LF_M = \frac{\sum_{SC} \min(0, DB_{SC} - DB_{SC, FCFS})}{\sum_{SC} DB_{SC, FCFS}}$$  

(1)

The results of the computational analysis are given in Table 2 and Fig. 11. Depicted are the results of the BPU-NN policy compared to RLP, RLP-R and BPU-NN for the 110%, low volatility demand level. Even with non-optimal basis bid-prices, BPU-NN yields average results which are better than those of RLP and RLP-R. However, the performance falls short on BPU-NN. The results of a risk analysis are depicted in Fig. 11. The risk associated with BPU-NN is comparable to that of RLP and higher than that of RLP-R. In contrast, BPU-NN helps to significantly reduce risk. For all cases considered, the LF value is superior to all other policies. Accordingly, there is a moderate trade-off between expected performance and risk.
The trade-off curve is illustrated in Fig. 12. Depicted is the performance of the different policies with respect to the two dimensions contribution margin and LF value. As can be seen, RLP and RLP-R are dominated by all BPU-NN policies. By shifting the BP, different efficient solutions can be generated. To identify the optimal policy, further knowledge on the level of risk averseness of the decision maker is required.

It can be derived that the presented approach is suited to actively managing risk. Risk can be reduced at a very moderate loss in expected revenue potential.

5. Conclusions and future research

In this paper, we addressed the capacity control problem in MTO revenue management under stochastic demand. We proposed an approach which takes into account the characteristics and information dynamics of MTO settings and updates the bid-price during the booking period based on online demand information. The result is a two-stage approach with a basis bid-price applied until the bid-price adjustment, followed by a scenario specific bid-price, determined by artificial neural networks. While the approach is motivated by the specific characteristics of MTO production, it is not limited to this industry setting. Adopting the approach to other industries like the airline industry offers promising avenues for future work.

The simulation results showed that the performance in terms of average contribution margin is quite robust. As compared to FCFS, the average improvement was 7.8–20.1%, depending on the demand setting. One adjustment during the booking period is sufficient to capture most of the revenue potential left untapped by traditional approaches like RLP. With respect to the theoretical optimum derived from the ex-post computation, the remaining gap was on average not larger than 1.3 percentage points. By limiting the number of updates, the two-stage approach at the same time allows for the transparent and stable coordination of the sales organization. In contrast to purely static approaches it incorporates current demand data. In order to proceed even further towards the theoretical optimum, the number of updates may be increased. This would allow for better incorporating the evolving informational basis. In particular we would expect improvements with respect to the worst case performance, which in selected demand realizations fell up to 9.5 percentage points short on the theoretical optimum.

Increasing the number of updates gives rise to two directions for future work. A first challenge is to incorporate the option of multiple updates into the computation of the basis bid-price and the updating procedure. This would require advancing the proposed offline and online procedure. Approaches from multi-stage stochastic programming [15,16] and simulation optimization [7] have proven helpful in similar settings. A second challenge results from the organizational setting of MTO companies. If bid-prices change dynamically, new instruments become necessary to coordinate sales. This in particular relates to incentive schemes, which are used to reward successful sales performance. From a methodological point of view, the question arises of how to assess customer request which are only confirmed after some evaluation phase of the customer. Since bid-prices may be updated between the request and the confirmation, it may be necessary to adjust the bid-price in correspondence with the evaluation time and the anticipated bid-price development. Methods to quantify this adjustment are missing.

The proposed bid-price approach depicts interesting characteristics for risk-adverse decision makers. By intentionally reducing the basis bid-price, the risk of falling below the performance of the naive FCFS policy can be controlled. According to the analysis, the proposed BPU-NN approach dominates the examined traditional bid-price policies in risk and expected contribution margin. To assess the properties of the approach in terms of risk, we constructed a trade-off curve between the expected contribution margin and the expected loss. Given this information, decision makers are provided with support in identifying the capacity control policy which best fits their preferences. An interesting opportunity for future work arises from the
more formal incorporation of risk into the determination of bid-prices. Since this incorporation constitutes a multiple criteria decision situation, approaches from multi objective decision making should be promising.

Although the focus of the analysis was on a somewhat simplified setting with a single bottleneck resource, we believe that the approach warrants interesting opportunities for application in industry. The use of formal revenue management methods in manufacturing is a rather young field. Accordingly, decision makers do not necessarily dispose of the same high level of expertise as in service industries. This requires approaches with a small number of parameters and a high level of automation respectively. Given a demand forecast and information on the availability of bottleneck capacity, the proposed approach provides a capacity control policy which outperforms existing revenue management approaches. The only additional parameter required is the interval boundary. If the general booking behavior, i.e. the ordering lead times, can be considered stationary, the interval boundary can be set once and does not require any adoption. In order to exploit the full potential of the approach, decision support on the determination of the interval boundary is necessary. Given that the determination of the optimal value is impractical [17], heuristics based on some aggregate representation of demand are a promising field for future work.

Acknowledgments

Second author's research was supported by TUBITAK-DFG (The Scientific and Technological Research Council of Turkey-Deutsche Forschungsgemeinschaft).

Appendix

See Tables 3–5.

Table 3
Neural network statistics.

<table>
<thead>
<tr>
<th>Demand level</th>
<th>Low volatility</th>
<th>High volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>110%</td>
<td>125%</td>
</tr>
<tr>
<td>Neural Network I</td>
<td>No. of hidden layer nodes</td>
<td>15</td>
</tr>
<tr>
<td>Neural Network II</td>
<td>No. of hidden layer nodes</td>
<td>11</td>
</tr>
<tr>
<td>Neural Network I</td>
<td>Classification accuracy on 200 demand realizations (%)</td>
<td>86</td>
</tr>
</tbody>
</table>

Table 4
Resulting bid-prices.

<table>
<thead>
<tr>
<th>Demand level</th>
<th>Low volatility</th>
<th>High volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>110%</td>
<td>125%</td>
</tr>
<tr>
<td>RLP (static) in EUR/h</td>
<td>1132</td>
<td>1912</td>
</tr>
<tr>
<td>Basis BP $t^*$ = 20 in EUR/h</td>
<td>1200</td>
<td>2000</td>
</tr>
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Table 5
Paired t-tests.

<table>
<thead>
<tr>
<th>110% LV</th>
<th>RLP</th>
<th>RLP-R</th>
<th>BPU-NN</th>
<th>BPU-EP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCFs</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>RLP</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>RLP-R</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>110% HV</td>
<td>RLP</td>
<td>RLP-R</td>
<td>BPU-NN</td>
<td>BPU-EP</td>
</tr>
<tr>
<td>FCFs</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>RLP</td>
<td>o</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>RLP-R</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>125% LV</td>
<td>RLP</td>
<td>RLP-R</td>
<td>BPU-NN</td>
<td>BPU-EP</td>
</tr>
<tr>
<td>FCFs</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>RLP</td>
<td>o</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>RLP-R</td>
<td>X</td>
<td>X</td>
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<td>X</td>
</tr>
<tr>
<td>125% HV</td>
<td>RLP</td>
<td>RLP-R</td>
<td>BPU-NN</td>
<td>BPU-EP</td>
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<tr>
<td>FCFs</td>
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</tr>
<tr>
<td>RLP</td>
<td>o</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>RLP-R</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

Statistical difference at 95% confidence level: $X =$ Yes, $o =$ No.

References


